A Fuzzy SMART Based Dynamic Decision Making System: A Voltage Control Case Study

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EXTENDED ABSTRACT

Most real-life decisions involve Dynamic Decision Making (DDM) that is characterised by the need to make multiple and interdependent decisions in an environment that changes as a function of the decision maker's actions, environmental events, or both. Some examples can be found in management of transportation networks and in controlling of power systems. To assist humans in these difficult decision making scenarios, computer-based decision making systems have been developed. Most of them rely on dynamic programming algorithms. Unfortunately, heavy computational burden makes them not suitable for application to large systems and precludes finding a solution in a limited time which is an important determinant of the performance.

This paper describes the development of a fuzzy Simple Multi-Attribute Rating Technique (SMART) based dynamic decision making system which incorporates the merits of human decision making mechanisms and operational research methods to find an optimal solution taking the least amount of time in a dynamic environment. To illustrate the proposed framework, we apply it to a practical voltage control problem in abnormal scenarios in power systems. The proposed system (see Figure 1) includes three components: a 'voltage monitor' to monitor abnormal voltage profiles based on a power flow algorithm, an 'evaluator' to evaluate the effectiveness of candidate control actions based on a SMART algorithm, and a 'decision maker' to search an optimal voltage control schedule based on a fuzzy linear programming algorithm.

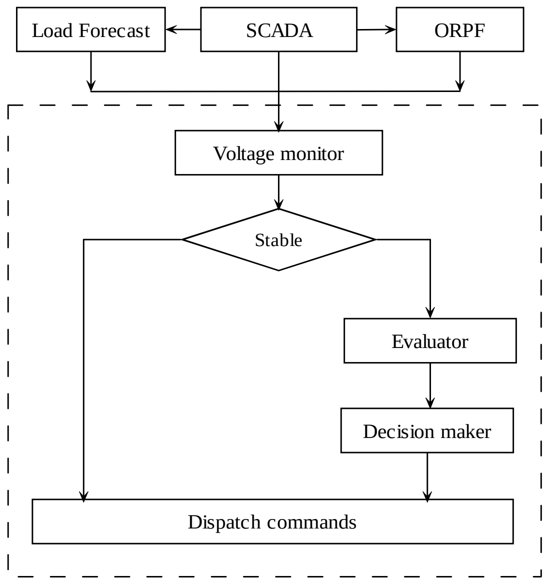

Figure 1. The Framework of the Proposed DDM system

We present the test results on a benchmark 9-bus test power system under a dynamic scenario caused by load demand variations. The results show that the proposed approach can quickly find optimal decisions for maintaining an acceptable voltage profile in a dynamically changing power transmission environment. Furthermore, it can reduce the number of unnecessary control actions in comparison to a traditional sensitivity based method. The proposed framework can be easily applied to other similar dynamic decision making problems, such as ordering system in industry.

1. INTRODUCTION

Most real-life decisions involve Dynamic Decision Making (DDM) that is characterized by the need to make multiple and interdependent decisions in an environment that changes as a function of the decision maker's actions, environmental events, or both (Edwards 1962). Some examples can be found in management of transportation networks and in controlling of power systems. The DDM is a challenging task for humans because of time pressure and dynamic complexity (Gonzalez 2005). An air traffic controlling task, for example, requires controllers to make dynamic decisions regarding how best to allocate landing lanes to incoming airplanes. The time pressure comes from the fact that incoming airplanes need to be assigned to a landing lane at the correct moment in real time. The dynamic complexity is reflected by the fact that the assignment of a landing lane to an incoming airplane precludes the use of that lane by other airplanes arriving in the near future. To assist humans in these difficult decision making scenarios, computer-based decision making systems have been developed.

The voltage control problem addressed in this paper is a complex DDM problem. The basic philosophy of this problem is to optimally allocate voltage control devices, such as, generators, capacitors, transformers, to keep an acceptable voltage profile in dynamic power systems. Two main dynamic factors (load demand variations and equipment failure), combined with the uninterruptible property of power, aggravate the difficulty. The increasing power demand on the existing power systems and the recent deregulations in power industry make power systems to operate near their voltage stability limits. This results in unacceptable voltage profile reported frequently, for example the severest August 14th blackout in the United States and Canada.

Over the last decades, the voltage control problem has been researched extensively as a static snap-shot optimization problem, named Optimal Reactive Power Flow (ORPF) (Sharif & Taylor 1997). The ORPF algorithm lacks flexibility in real time operation. The reasons are that the nonlinear programming problem – ORPF, requires long computation time and every control variables should be readjusted in every round. The excessive adjustments increase operators' workload and decrease the operation life of the expensive control devices. Recently, Sharif et al. (2000) proposed some strategies for real-time implementation of ORPF. In their approach, only a few most important control variables, which is decided based on some heuristic rules, were adjusted every time. However, these heuristic rules cannot accurately cover all the operation scenarios.

This paper proposes a fuzzy Simple Multi-Attribute Rating Technique (SMART) based dynamic decision making system to reschedule control actions against unexpected scenarios. The SMART technique is utilized to deal with the dynamic complexity through evaluating both the current effectiveness and future effectiveness of candidate control actions; while the simple linear optimization model is adapted to release the computation burden, that is, save the computation time. The effectiveness has been proved on a 9-bus benchmark test system. The results show that the proposed approach can quickly find optimal decisions for maintaining an acceptable voltage profile in a dynamically changing power transmission environment.

The rest of the paper is organized as follows: Section 2 describes the structure and related techniques of the proposed framework. Section 3 presents the results performed on a 9-bus benchmark test system under unexpected scenarios, such as load demand variations. Finally, concluding remarks is given in Section 4.

2. SYSTEM DESCRIPTION

The proposed system is an artificial intelligence based DDM system used to maintain an acceptable voltage profile against unexpected scenarios in transmission networks of power systems. A general overview of the proposed control system is shown in Figure 1. The proposed system includes three components: a voltage monitor to monitor abnormal voltage profiles based on a power flow algorithm, a information synthesizer to evaluate the effectiveness of candidate control actions based on a SMART algorithm, and a decision maker to search an optimal voltage control schedule based on a fuzzy linear programming algorithm. The proposed system interacts with three external programmes: a load forecast package, a SCADA (Supervisory Control And Data Acquisition), and an ORPF package. The functions of these external packages are:

- The load forecast package provides the load forecast information;
- The SCADA is a real time monitoring system for power systems which can reflects the status of the operating system;
- The ORPF package is based on a multi-stage optimization technique which determines the future long-term control

schedule for voltage control (This was developed as a part of this study and discussed in details in (Lin, Samarasinghe, & Hu 2004)).

The working procedure of the proposed system is as follows. Firstly, the voltage monitor continuously monitors the current voltage profile based on the data provided by the SCADA and tests voltage profile in the near future (2 minutes later) based on the forecasted load demand and the predefined control schedule decided by the ORPF package. If the voltage profile in both case (the current and the near future) is satisfactory, the predefined control schedule then will be directly dispatched. Otherwise, the control schedule will be adjusted by the evaluator and the decision maker components to eliminate the unsatisfactory voltage problem. In the evaluator, a set of candidate control actions are rated for both short-term and long-term effectiveness. Finally, the new control schedule, which removes the unsatisfactory voltage problem, is derived by the decision maker.

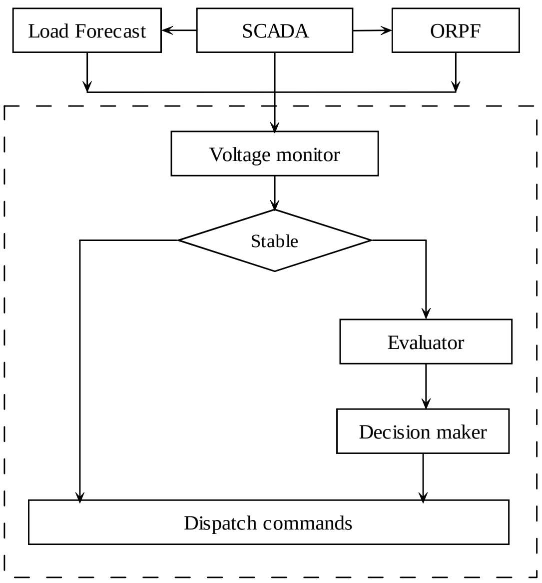

Figure 1. The Block Diagram of the Proposed DDM system

2.1. Voltage Monitor

The voltage monitor is based on the Newton-Raphon power flow algorithm (Kundur, Balu, & Lauby 1994). The power-flow (also called load-flow) is a useful tool to study the behaviour of a power system since it can calculate power flows and voltages of a transmission network for specified terminal or bus conditions. The state of each bus in a power system can be characterized by four variables: voltage magnitude V, voltage angle δ, real power injection P and reactive power injection Q. The relationship of these four variables in every bus can be formulated by the power-flow equations, which are derived form the Tellegen's theorem or power theorem in circuit theory (Glover & Sarma 2002). The theorem states that the total summation of power injection into a bus or a node from all connected branches must be equal to zero. Then for each bus, there is:

$$P_i + jQ_i = \overline{V}_i * \overline{I}_i^* \qquad (1)$$

where

P_i = real power generation at bus i;

Q_i = reactive power generation at bus i;

$\overline{V}_i$ = voltage vector at bus i;

$\overline{I}_i$ = current vector at bus i.

These set of nonlinear power flow is solved by the powerful Newton-Raphson method. Then, the voltage profile in the near future can be decided based on the load forecast and the predefined control schedules.

2.2. Evaluator

The evaluator innovatively applies the Simple Multi-Attribute Rating Technique (SMART) in evaluating the candidate control actions in voltage control. The SMART algorithm is a well-known method for Multi-Criteria Decision Analysis (MCDA) which considers how to evaluate a finite number of decision alternatives under a finite number of performance criteria. The SMART has been successfully applied in many areas, such as, ordering system in industry (Cheema & Naim 1995) and the public health planning (Van Gennip, Hulshof, & Lootsma 1997).

The central idea of SMART is to transform the quantitative or qualitative value in different performance criteria into a new subjective dimension of desirability based on Weber's psychophysical law of 1834 (Lootsma 1997). Then a final grade can be assigned by the arithmetic-mean aggregation rule. In the dynamic emergency voltage control problem, the SMART is used to rate the candidates under two performance criteria: short-term and long-term effectiveness. The short-term effectiveness is the current sensitivity between the candidate and the voltage magnitude in targeted bus. The sensitivity can be derived from the power flow program in the voltage monitor. The other criterion, the long-term effectiveness, is measured by the timing in the original predefined plan. The reason is that the predefined plan is optimally decided based on the long-term (24 hours) load forecast which does not deviate in great extent, normally within 10%.

The Weber's psychophysical law is an approximate psychological law relating the degree of response or sensation of a sense organ and the intensity of the stimulus. The law asserts that the just noticeable difference in stimulus intensity must be proportional to the actual stimulus intensity itself. When this law is applied in MCDA, the response of a sense organ represents the subjective human's desirability and the intensity of the stimulus means the quantitative value in a special performance criterion, for example, the timing and sensitivity value in this study. Their relationship can be expressed by one of the following two mathematical formulae according to whether the most subjective desirability corresponds to the upper or lower end of the range for the quantitative value (stimulus). If the most desirable target is at the lower end of the quantitative value range [Q_{min}, Q_{max}], there is

$$v = \log_2\left[\frac{Q_v - Q_{\min}}{Q_{\max} - Q_{\min}} \times 2^6\right], v = 0,1,\ldots,6. \qquad (2)$$

where

Q_v = the quantitative value in a special performance criterion;

v = the order of the magnitude in desirability dimension and its maximum is set to 7 according to the seven-point scale method in behavioural science (Lootsma 1997).

If the most desirable target is at the upper end of the quantitative value range [Q_{min}, Q_{max}], there is

$$v = \log_2\left[\frac{Q_{\max} - Q_v}{Q_{\max} - Q_{\min}} \times 2^6\right], v = 0,1,\ldots,6. \qquad (3)$$

The short-term desirability can be calculated by (3) since a large sensitivity factor is preferred; while the long-term desirability is based on (2) since a small timing adjustment is more desirable. Now, every candidate control action is measured in one common subjective desirability dimension instead of two different performance criteria. The advantage of this transition is that the order of the magnitude in desirability can be aggregated to compare the performance of the candidates.

The aggregation is achieved through the arithmetic-mean aggregation rule:

$$s_j = \sum_{i=1}^{m} c_i v_{ij}, j = 1,\ldots,n, \; and \sum_{i=1}^{m} c_i = 1 \qquad (4)$$

where

i = the index of the different criteria;

j = the index of the candidate control action set;

s_j = the overall grade for the j candidate;

c_i = the normalized weight for the i criterion;

v_{ij} = the desirability grade of the j candidate under the i criterion.

The final grades represent the overall performance of the candidates under all the criteria.

2.3. Decision Maker

The purpose of the decision maker is to find the optimal settings for the most desirable control candidates based on a fuzzy linear programming algorithm. This algorithm incorporated the fuzzy set theory into the traditional linear programming algorithm to model the uncertainty of the voltage control problem, such as the sensitivity factor between the control devices and the voltage of the targeted bus. The sensitivity factors are the simplified linearized approximation of their nonlinear relationship. Therefore, there is uncertainty about the value of the sensitivity which cannot be represented by the ordinary crisp set which has a unique binary membership function. The fuzzy set theory was developed by Zadeh in 1965 as a mathematical tool for modelling the inexactness and uncertainty concerning decision-making (Momoh & El-Hawary 2000).

The fuzzy set is a generalization of the classical crisp set theory in the sense that the domain of the characteristic function is extended from the discrete set {0, 1} to the closed real interval [0, 1]. The fuzzy set can be characterized by the set of pairs

$$A = \{X, \mu_A(X), x \in X\} \qquad (5)$$

where X is a set of objects, called the universe, whose element are denoted as x. $\mu_A(X)$ is named membership function whose value indicates the grade of membership x in A. The closer the value of $\mu_A(X)$ is to 1, the more x belongs to A. Now any sensitivity factor x is not necessarily a fixed number. In contrast, it may take any value within a range that contains the most possible (likely) value. A fuzzy membership $\mu_A(X)$ can then represent the degree of membership of X with the most likely value of X having a degree of membership of 1.0. This idea is the more accurate description of the nature of the sensitivity factors. The fuzzyfied numbers representing the sensitivity factors are called fuzzy numbers in fuzzy set theory. A typical triangular fuzzy number representing a sensitivity factor, which is equal to 2, is shown in Figure 2. The fuzzy sensitivity means that the value of sensitivity lies in the range [1.95, 2.05] and the most possibility is 2 where its membership is 1.

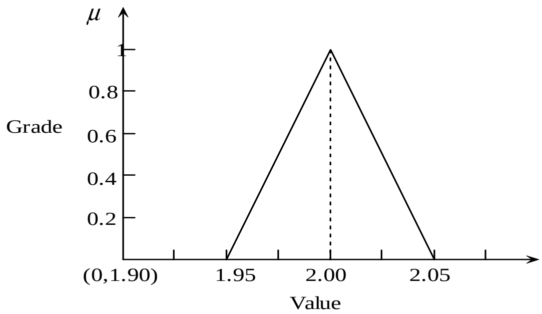

Figure 2. A Typical Fuzzy Number 2

Besides the extension of the crisp set-theoretic operations, the fuzzy set theory also develops algebraic operations and hence permits the use of fuzzy numbers for optimization. The fuzzy optimization model, embedded in the decision maker, is as follows:

$$\begin{aligned} &\text{max:} && CX \\ &\text{subject to:} && AX \;\tilde{\geq}\; B \\ & && 0 \le X \le X_{max} \end{aligned} \tag{6}$$

where
C = the vector of the desirability parameters;
X = the vector of the control variables;
B = the vector of the constraints;
A = the matrix of the sensitivities.

In this fuzzy model, the C, A, and B are all expressed by the triangular fuzzy numbers. Like the sensitivity B, there are uncertainties associated with the desirability C and constraints B. Also, the inequality $\tilde{\geq}$ is the fuzzy inequality which will be discussed later. The meaning of this model is to maximize the control desirability while satisfying the voltage profile constraints. The constraints should include not only the correction to the damaged voltage profile but also the prevention of new problems in other areas. The advantage of the fuzzy model is that all kinds of uncertainties in voltage control are incorporated into the model.

One effective solution of the fuzzy linear programming is the symmetric model proposed by Bellman and Zadeh (Bellman & Zadeh 1970). In their symmetric model, there is no difference between objectives and constraints both of which are characterized by their membership functions. Thus, the fuzzy optimization problem is transformed to a constraint satisfaction problem as follows.

$$\begin{aligned} &\text{Fuzzy goal:} && a_{11}x_1 + \ldots + a_{1n}x_n \;\tilde{\geq}\; b_1 \\ &\text{Fuzzy constraint:} && a_{21}x_1 + \ldots + a_{2n}x_n \;\tilde{\geq}\; b_2 \\ & && \vdots \qquad\quad \vdots \qquad\quad \vdots \quad\;\; \vdots \\ &\text{Fuzzy constraint:} && a_{m1}x_1 + \ldots + a_{mn}x_n \;\tilde{\geq}\; b_m \end{aligned} \tag{7}$$

where b_1, called the aspiration level, is the maximum value of their equivalent crisp model. Also, this fuzzy model can be expressed in a simplified form:

$$y_i = a_{i0}x_0 + a_{i1}x_1 + \ldots + a_{in}x_n \;\tilde{\geq}\; 0, \; i = 1,\ldots, m. \tag{8}$$

where $a_{i0} = -b_i$ and $x_0 = 1$. a_{ij}, for i = 1,…, m, j = 1,…, n, are triangular fuzzy numbers with center α_{ij} and width d_{ij}. The membership function of y_i can be obtained as:

$$\mu_{y_i}(y) = 1 - \frac{\left| y - \sum_{j=1}^{n} \alpha_{ij} x_j \right|}{\sum_{j=1}^{n} d_{ij} x_j} \tag{9}$$

The fuzzy positive is defined by:

$$y_i \;\tilde{\geq}\; 0 \Leftrightarrow \mu_{y_i}(0) \le 1 - h, \sum_{j=1}^{n} \alpha_{ij} x_j \ge 0, \tag{10}$$

where h stands for the degree of $y_i \;\tilde{\geq}\; 0$ and the larger the h is, the stronger the meaning of "almost positive" is (see Figure 3).

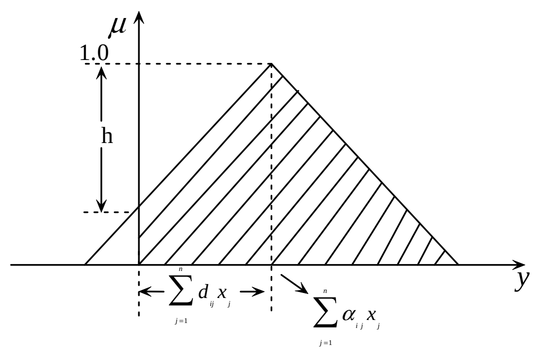

Figure 3. The Explanation of Fuzzy Positive

According to this definition, the inequality equation (8) turns out to be:

$$\mu_{y_i}(0) = 1 - \frac{\sum_{j=1}^{n} \alpha_{ij} x_j}{\sum_{j=1}^{n} d_{ij} x_j} \le 1 - h, \sum_{j=1}^{n} \alpha_{ij} x_j \ge 0, \qquad (11)$$

where x ≥ 0. The above inequalities come out simply as follows:

$$\sum_{j=1}^{n} (\alpha_{ij} - hd_{ij}) x_j \ge 0, i = 1, ..., m. \qquad (12)$$

As mentioned in (10), the fuzzy optimization problem is to maximum the value of h satisfying m number of inequalities in (12). In other words, we need to solve the following problem:

max: h (13)

s.t.: $\sum_{j=1}^{n} (\alpha_{ij} - hd_{ij}) x_j \ge 0, i = 1, ..., m.$

$0 \le h \le 1$

Now, the fuzzy optimization problem is simplified to a nonlinear programming problem which is solved by the Sequential Quadratic Programming (SQP) algorithm in the optimization toolbox of MATLAB (*Optimization toolbox user's guide* 2004). After this problem is solved, a solution, considering the ambiguity of all the coefficients simultaneously, can be obtained. The solution should be verified by the power flow algorithm in the voltage monitor before it is dispatched due to the high nonlinearity in the voltage control. In some worst cases, the algorithm may be repeated to find a satisfactory solution.

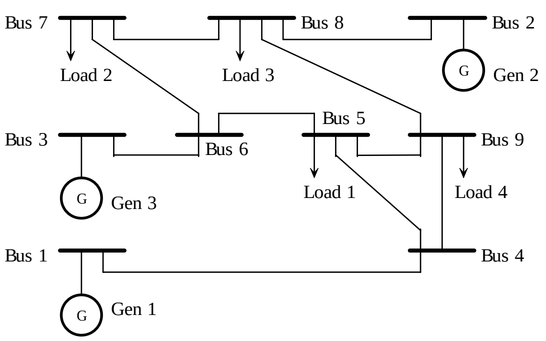

Figure 4. The 9 – bus Test System

3. CASE STUDY AND RESULTS

To verify the effectiveness of the proposed method, a 9-bus test system (see Figure 4) given by Matpower (Zimmerman & Gan 1997) is analysed in a dynamic load demand scenario. The test system consists of 3 generators which are the voltage control devices for the system and 9 buses. The security voltage operation region is between 0.97pu and 1.04pu.

The dynamic scenario is described as follows. According to the load forecast (see Table 1), a predefined control schedule for the next three time stages (see Table 2) is decided by the ORPF algorithm. However, the practical load demand at the first stage increases by more than expected which causes an unacceptable low voltage (0.969pu) at bus 9 (Table 3). Therefore, a revised control plan should be made to remove the problem.

Table 1. The Dynamic Load Demand

Load bus	Forecast load			Practical load
	Stage 1	Stage 2	Stage 3	Stage 1
1	90+30j	100+33j	110+36.3j	94.5+31.5j
2	100+35j	110+38.5j	121+42.35j	105+36.75j
3	0	0	0	90+30j
4	125+50j	137.5+55j	151.25+60.5j	170+52.5j

* The unit of real power is MW and the unit of reactive power is MVAR.

Table 2. The Control Plans

Stage	Control settings		
	Original Plan	Proposed method	Traditional method
1	V_{G1} = 1.030pu V_{G2} = 1.030pu V_{G3} = 1.022pu	V_{G1} = 1.030pu V_{G2} = 1.030pu **V_{G3} = 1.026pu**	**V_{G1} = 1.031pu** V_{G2} = 1.030pu V_{G3} = 1.022pu
2	V_{G3} = 1.026pu	No action	V_{G1} = 1.030pu V_{G3} = 1.026pu
3	V_{G3} = 1.030pu	V_{G3} = 1.030pu	V_{G3} = 1.030pu

Table 3. System Voltages (before and after voltage correction)

Bus number	Intitial voltage	Final voltage (Version one)	Final voltage (Version two)
1	1.030pu	1.030pu	1.031pu
2	1.030pu	1.030pu	1.030pu
3	1.022pu	1.026pu	1.022pu
4	1.006pu	1.007pu	1.007pu
5	0.994pu	0.996pu	0.995pu
6	1.019pu	1.022pu	1.019pu
7	0.995pu	0.997pu	0.995pu
8	1.003pu	1.004pu	1.004pu
9	**0.969pu**	**0.970pu**	**0.970pu**

Results from the proposed method are presented in Table 2 along with the results from traditional sensitivity based method for comparison. The voltage profiles after control are shown in Table 3. It shows that the final voltages under both methods are within acceptable limits ($0.97_{pu} \leq V \leq 1.04_{pu}$). The difference is that the proposed method used less number of control actions than the traditional method used as shown in Table 2. The reason is that the former considers the interdependent relationship in the dynamic power transmission environment while the latter only focus on a static state. In consequence, the overall performance of the proposed method is better than the traditional sensitivity based method.

4. CONCLUSIONS

In this paper, a fuzzy SMART based DDM system is presented and applied to a complex DDM problem – voltage control in power transmission systems. There are two difficulties: time pressure and dynamic complexity associated with the voltage control, similar to other DDM problems. To deal with the dynamic complexity, a multi-criteria decision analysis method – SMART is innovatively applied to quickly evaluate the performance of control actions in the dynamic power transmission environment. This technique can compute an overall desirability for each candidate under two criteria (short-term and long-term effectiveness). After that, a fuzzy based optimization model, which incorporates the uncertainties in parameters, is built to find the optimal revision plan to reach the desired voltage profile. The results show that the proposed method can use less number of control actions to correct the unacceptable voltage problem in comparison to the commonly used method – the sensitivity based technique which is a static method and does not consider the dynamic complexity. The reduction in number of required control actions helps reduce both the work load of operators and depreciation cost of control equipment. Further, the proposed framework can be adopted to other similar dynamic decision making problems, such as ordering system in industry. The next stage of this project will include an implementation of the proposed system in the real-time operating environment.

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